Studies on Eco-Friendly Pest Monitoring Through Acoustic Technology

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ABSTRACT

This study investigates how acoustic sensors can transform sustainable pest monitoring by providing a real-time, non-invasive substitute for conventional pest management methods, which are frequently imprecise and chemical-dependent. Acoustic sensors provide constant monitoring and early infestation detection by identifying pests by their unique sound patterns. In order to improve data collection, real-time analysis, and automated decision-

making, this study looks at current developments in MEMS-based acoustic sensors and how they integrate with IoT networks. System optimization, ambient noise filtering, scalability, and affordability, especially for small-scale farmers, are the main topics of discussion. According to research, acoustic pest detection in association with machine learning algorithms can increase the accuracy of insect classification, reduce the need for pesticides, and facilitate more flexible and economical integrated pest control systems.

Keywords - *Eco-friendly pest monitoring, Acoustic technology, Pest detection, Acoustic sensors, Sustainable agriculture, Wireless sensor networks*

1. INTRODUCTION

One of the biggest issues faced in modern agriculture is ensuring food security for a growing world population while reducing environmental concerns. Crop yields are still seriously threatened by pests, and conventional pest management techniques like chemical pesticides can have unforeseen consequences like environmental contamination, health risks, and pesticide resistance. These problems show how urgently eco-friendly and sustainable pest control methods are needed.

Innovative solutions have been made possible by emerging technologies, and acoustic sensing is becoming more and more popular as a real-time, non-invasive approach to pest identification. Through sound analysis, acoustic sensors especially those built on MEMS (Micro-Electro-Mechanical Systems) technology offer an excellent sensitivity and versatility for tracking insect activity. These systems reduce the need for hazardous pesticides by enabling automated pest identification, classification, and management when combined with IoT and machine learning algorithms.

Recent developments have shown how effective these systems may be in a range of agricultural contexts. Widespread adoption is still significantly hindered by issues including restricted expandability, expensive implementation costs, and interference from background noise. The results of modern research on acoustic pest monitoring are summarized in this study, focusing on the function of hybrid sensor systems, machine learning methods, and IoT integration. In order to increase the effectiveness and accessibility of acoustic pest management systems for sustainable agriculture, the article also examines current drawbacks and possible fixes.

2. LITERATURE REVIEW

2.1 Sensor – based pest detection

A wide range of sensor types are being investigated for their potential in detecting pest activity using acoustic signals, marking a considerable evolution in sensor-based technologies for pest detection in recent years. Using MEMS microphones, which can identify pest-specific sound characteristics, is a crucial field of research. Savanne Remy Kham *et al.* (2022), for example, investigated MEMS-based sound level monitoring systems, concentrating on their capacity to detect frequencies linked to insect infestations. Using IoT-enabled acoustic sensors, Rajesh Kumar *et al.* (2023) also used deep – learning approaches to improve the accuracy of pest detection. These developments suggest that MEMS sensors and advanced algorithms present a effective way to detect pests in agricultural environments in real time.

2.2 Integration of IoT and wireless sensor networks

Adaptable pest management systems have been made possible by the combination of wireless sensor networks (WSNs) and the Internet of Things (IoT). According to Saeed Azfar *et al.* (2023), WSNs are crucial for pest identification since they can provide precise, up-to-date data over wide agricultural areas. Furthermore, especially in big or rural farming contexts, the use of distant communication technologies, such LoRa, has been investigated for remote data transfer. LoRa-based IoT networks have been shown in studies by Yik-Tian Ting *et al.* (2024) to maximize sensor network performance for smart farming. With the use of these technologies, farmers can keep an eye on insect activity across long distances, enabling more effective and targeted pest management strategies.

2.3 Acoustic pest monitoring

The ability of acoustic monitoring to identify pests by their unique sounds is becoming more widely recognised. According to research on tropical insect conservation by Klaus Riede *et al.* (2022), pests' acousticsignatures may be utilized for early detection. In a similar vein, Jelto *Branding et al.'s* (2023) InsectSound1000 dataset is a useful tool for machine learning model training. Numerous pest sounds are included in this sizable, annotated collection, which can be utilized to enhance detection systems. The ability to identify pest-related audio characteristics over background noise is one way that this kind of data-driven strategy improves the efficiency of acoustic monitoring.

2.4 Deep – learning and Machine – learning techniques

Techniques for machine – learning (ML) and deep – learning (DL) have transformed agricultural pest identification in recent years. These innovative technologies make it possible to analyze complicated data, such as environmental sensor readings, visual data from cameras, and acoustic signals all of which are essential components of pest monitoring systems.

In pest detection systems, the use of MEMS microphones for sound analysis has drawn a lot of interest. Convolutional Neural Networks (CNNs) and other deep – learning models can be used to interpret the audio information that these microphones record from pests. According to Gopalakrishnan Nagaraj *et al.* (2023), for example, cotton pests can be identified using CNNs by their distinct acoustic signals. This method eliminates the need for time-consuming manual inspection and provides an effective, non-invasive method of pest monitoring. The accuracy of pest detection models can be greatly increased by using environmental variables like temperature, humidity, and soil moisture in addition to sound data.

2.5 Limitations and challenges in current research

There are a number of reasons why present research on sensor-based pest monitoring is limited and difficult. The sensors' high sensitivity to ambient noise is a major problem that may hinder precise pest identification. This is especially noticeable in acoustic monitoring systems, where signals linked to pest activity might be interrupted by background noise from wind, industry, or other species. In order to address this, scientists have concentrated on sophisticated signal processing methods like wavelet transforms and noise filtering algorithms; however, these approaches are still developing and might not work in every agricultural setting (Riede *et al*., (2022); Azfar *et al*., (2023)). Furthermore, sensor networks frequently have power consumption issues, particularly when they are spread throughout huge agricultural regions with little access to electricity. Low-power communication technologies like LoRa have been developed in response to this challenge, but network scalability and energy efficiency are still major problems (Kham *et al*., (2022); Ting *et al*., (2023)).

The integration of several sensor technologies to develop comprehensive pest monitoring systems presents another difficulty in the industry. The compatibility of these various sensors frequently presents technical challenges, even though integrating acoustic, environmental, and optical sensors can improve detection accuracy. Moreover, operational challenges arise when sensor networks are deployed and maintained in extensive or remote agricultural areas. Small-scale farmers may find the expense of installing numerous sensors and the difficulty of handling and evaluating the data to be unaffordable (Bhairavi *et al.,* (2021)). Research is still being done to improve sensor durability, lower prices, and provide more reliable data analysis methods in order to overcome these obstacles.

2.6 Gaps in the literature

There are still a lot of gaps in the literature despite the advances in pest monitoring methods. The inadequate integration of multi-sensor systems that can offer a comprehensive approach to pest detection is one of the main drawbacks. Studies examining the combined use of acoustic, environmental, and optical sensors for more precise and dependable pest detection are scarce, despite their independent exploration (Kham *et al*., (2022); Bhairavi *et al*., (2021)). Additionally, studies frequently fail to consider how these technologies might be used in large-scale agricultural settings, where problems with sensor placement, upkeep, and data analysis are still unsolved (Zhang *et al*., (2023)).

2.6.1.Lack of integration of multi – sensory data

Research on integrating these data streams to increase detection accuracy is frequently lacking, despite the fact that many studies concentrate on specific sensor types (such as visual or audio sensors). For more reliable pest management solutions, combining several sensor types (such as temperature, humidity, and sound) into a single system may present a limitation.

2.6.2.Lack of standardization in sensor calibration and data analysis methods

Studies frequently use different sensor calibration techniques, as the literature review points out, making cross-references difficult. One important gap that may need to be filled is the establishment of uniform protocols.

2.6.3.Scalability and cost – effectiveness

A large number of current studies concentrate on small-scale or laboratory applications. Research is necessary, however, to make sensor-based pest detection systems scalable and reasonably priced for big farms, particularly in developing nations where cost is a key factor.

2.6.4.Real – time decision support systems Although sensor-based pest detection has advanced, real-time decision-making systems for pest control have yet to fully utilize this data. Systems that can automatically initiate actions, including turning on pest control technologies, in addition to detecting pests may be the subject of future research.

3.ACOUSTIC SENSOR TECHNOLOGY : AN OVERVIEW

Using sound waves to identify and categorize pests according to their distinct acoustic signatures, acoustic sensor technology has become a key element in agricultural pest monitoring. An outline of the types, important elements, historical evolution, and most current advancements in acoustic sensor technology are given in this section.

3.1. Historical developments in Acoustic sensors

Since early 20th-century research on pest behaviour, sound has been used to track insect activity. However, acoustic sensing has been transformed by technical developments in micro-electromechanical systems (MEMS) over the last few decades. The construction of small, sensitive, and affordable microphones was made possible by MEMS technology, as demonstrated by research conducted by Hermawanto *et al.* (2022) and Ozevin *et al.* (2018). Their incorporation into real-time pest monitoring systems was made possible by these advancements.

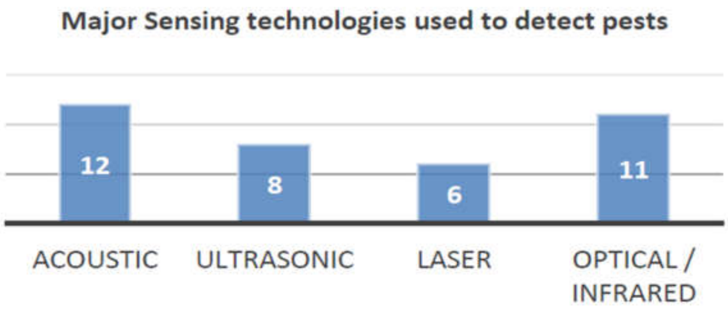

Figure 1 **-** Major sensing technologies used in agriculture. Adapted from Azfar S., Nadeem Al Hassan A., Alkhodre A., Ahsan K., Mehmood N., Alghmdi T., Alsaawy Y., 2018. Monitoring, detection, and control techniques of agricultural pests and diseases using

3.2. Types of acoustic sensors in agriculture

In agricultural contexts, a variety of acoustic sensor types are used, each with a distinct purpose. Due to their compact size and low power consumption, MEMS microphones are widely employed. Kham *et al.* (2022) have shown that these are perfect for identifying low-frequency noises made by pests.

Piezoelectric sensors are well-known for their great sensitivity and durability, making them ideal for picking up on minute vibrations brought on by pest activity.

According to Riede *et al.* (2021), directional microphones are used to concentrate on sound sources coming from particular directions while minimizing interference from background noise.

3.3. Key components and principle

The basic concept of acoustic pest monitoring is to record the sound waves produced by pests, convert these analog signals into digital formats, and then use algorithms to process the data in order to identify pest species. Crucial components include:

- Sound Capturing Element: Sound vibrations are recorded by the principal sensor, such as a MEMS microphone.
- Signal Conditioning: It is the preprocessing of signals, such as filtering and amplification, to improve the quality of the data.

As demonstrated in the work by Kumar *et al.* (2021), data processing units are frequently integrated with machine learning algorithms for real-time categorization and analysis.

3.4. Recent innovation and future discussion

Recent studies have looked into combining deep learning models with Internet of Things (IoT) frameworks to increase the accuracy and scalability of acoustic monitoring systems. Zhang *et al.* (2022) developed advanced neural network topologies for real-time pest identification that improved accuracy in noisy environments.

Researchers like Mahbub *et al*. (2021) anticipate that acoustic sensors will get increasingly smaller and more affordable in the future, enabling their widespread application. The development of solar-powered sensors and adaptable algorithms that can learn from different agricultural situations is expected to impel the next stage of innovation.

4. METHODOLOGY

With an emphasis on MEMS-based microphones and their uses in agriculture, this study was carried out by thoroughly examining a few chosen papers investigating the use of wireless sensor networks (WSNs) and acoustic sensors in pest detection. In order to gather important information about sensor technology, deployment tactics, and the function of data processing in pest management, the methodology for this study comprised a methodical review of these publications.

4.1 Data collection tools

Various tools were used in the reviewed studies to capture sound and collect data on pest activity. These instruments included:

- MEMS-Based Microphones: Highly sensitive sensors capable of detecting minute sound variations associated with pest movement and activity. These microphones are widely used due to their compact size and low power consumption.
- Piezoelectric Sensors: Used for detecting vibrations generated by pests within plant structures. These sensors convert mechanical vibrations into electrical signals, making them suitable for capturing low-frequency sounds.
- Directional Microphones: Designed to focus on specific sound sources, reducing interference from background noise and enhancing pest sound detection accuracy.
- Hydrophones: In studies involving pests in aquatic environments or high-moisture conditions, hydrophones were used to detect pest-generated acoustic signals.
- Optical and Laser-Based Acoustic Sensors: Some research employed laser Doppler vibrometer to measure surface vibrations caused by pest activity, offering non-contact detection capabilities.

These tools were integrated into various experimental setups, including field trials and controlled laboratory environments, to ensure comprehensive data collection.

4.2. Data collection methods

Field experiments and laboratory-based simulations were the two main data gathering strategies used in the examined studies. In order to identify pest sounds or other acoustic indicators linked to pest activity, sensors were placed in agricultural settings for field tests. This research paid special attention to crops like vegetables, rice, and cotton. Real-world testing of sensor performance in noisy agricultural settings was made possible by the field trials.

For example, Klaus Riede *et al.* (2021) employed acoustic monitoring to track tropical insect populations in protected environments, while Gopalakrishnan Nagaraj *et al.* (2022) investigated the use of convolutional neural networks (CNNs) for analysing sound signals obtained from MEMS microphones placed in cotton fields.

To test the sensitivity and specificity of sensors, controlled environments were constructed in laboratory simulations. To record sound waves produced by pests or environmental conditions, these investigations usually employed MEMS microphones or acoustic emission sensors. In-depth testing was carried out in studies such as Denny Hermawanto *et al.* (2020) and Morten Opprud Jakobsen *et al.* (2022) to gauge the frequency response of MEMS microphones and their capacity to differentiate between background noise and pest sounds. The signal-to-noise ratio (SNR), pest detection accuracy, and sensor performance in various environmental settings were evaluated using the data gathered from these tests.

4.3. Data analysis and processing

Following data collection, the acoustic waves were analysed using a variety of data processing techniques. Several studies used machine learning techniques to preprocess raw audio data in order to identify and categorize insect sounds. For example, Rajesh Kumar *et al.* (2021) applied deep – learning techniques to train a system capable of detecting pest-related sounds in agricultural areas using acoustic sensor data.

To convert unprocessed acoustic impulses into data that could be understood, sound analytics techniques such as spectrogram analysis were frequently employed. A visual representation of sound frequencies over time is offered by spectrograms, which can be examined to identify certain trends suggestive of pest activity.

The integration of acoustic sensors with Internet of Things (IoT) frameworks to provide real-time pest monitoring was also covered in a number of studies. Chandra Prakash (2023) and Mahbub (2021) investigated the use of sensors in conjunction with wireless communication technologies such as Wi-Fi and LoRa (Long Range) to establish networks that could send data over vast agricultural areas. In order to process data locally before sending it to central systems, edge computing was incorporated into sensor networks in certain experiments. This eliminated the need for high-bandwidth transmission and guaranteed quicker reaction times.

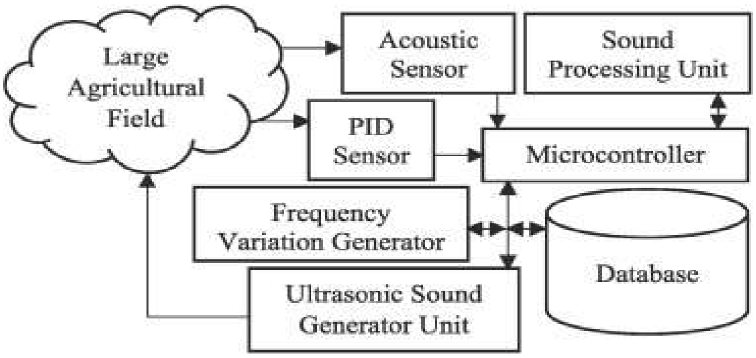

Figure 2 - System training using deep-learning techniques. Adapted from Ali Md., Rajesh Kumar D., Seifedine Kadry, 2024. AI-enabled IoT-based pest prevention and controlling system using sound analytics in large agricultural field. Computers and Electronic in Agriculture. 2024:220:108844.

Studies examining huge datasets frequently used neural networks and AI-based classifiers. For instance, Gopalakrishnan Nagaraj *et al.* (2022) used CNN-based models to identify insect sounds, obtaining high detection accuracy, while Shanwen Zhang *et al.* (2020) created a multi-scale attention U-Net architecture for crop insect identification. In order to increase the algorithms' accuracy in real-world situations, these machine learning models were trained using labelled acoustic datasets, which included annotated sounds made by different pests.

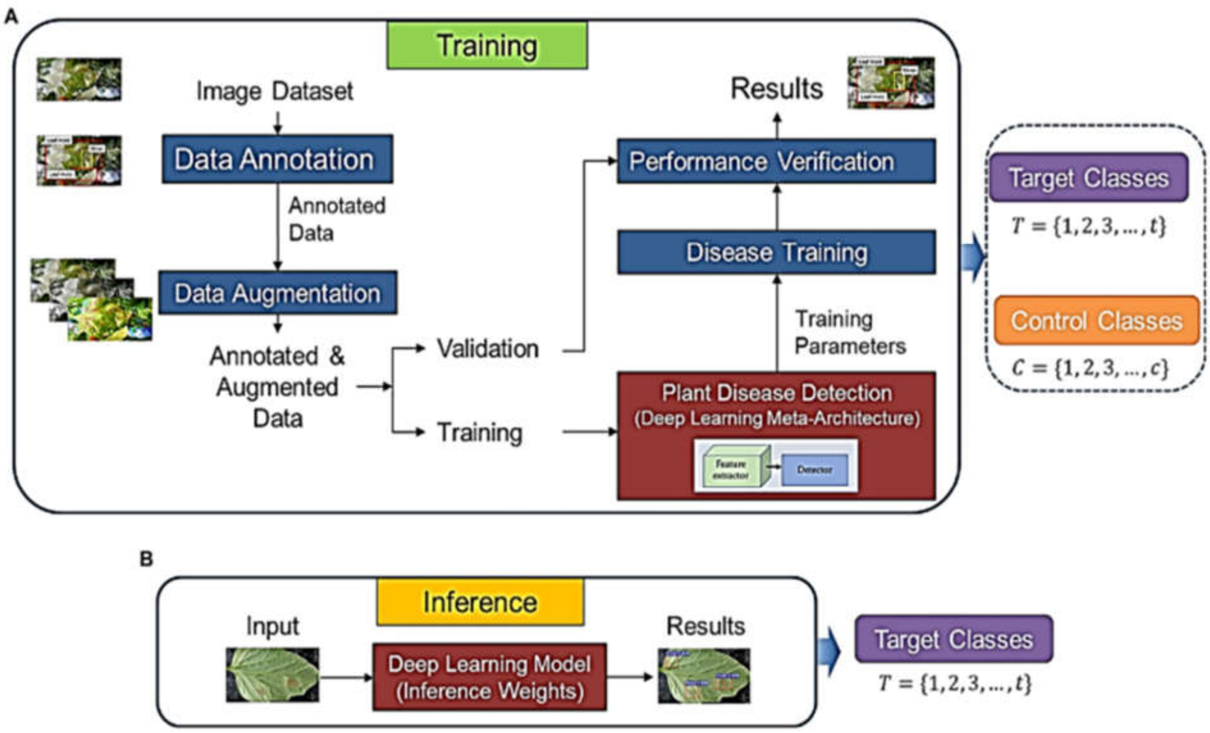

Figure 3 **-** Flowchart of CNN Classification: [A] The training process; [B] Data validation. Adapted from Fuentes A., Yoon S., Lee M., Park D., 2021. Improving Accuracy of Tomato Plant Disease Diagnosis Based on Deep Learning with Explicit Control of Hidden

4.4.Sensor calibration and evaluation

Accurate and trustworthy pest identification in agricultural applications depends on the calibration and assessment of sound sensors. Accurate calibration reduces measurement errors and accounts for environmental factors that can alter sensor data, such as wind, humidity, and temperature. The performance of MEMS microphones and other acoustic sensors for pest detection has been optimized by addressing these challenges in a number of research, which are detailed in this section.

4.4.1.Sensor calibration techniques

For acoustic sensor data to be as accurate and precise as possible, calibration is necessary. Numerous research has emphasized particular methods for calibrating MEMS microphones to address issues including dynamic range, frequency response, and interference from ambient noise. To determine the frequency response of MEMS microphones, for example, Hermawanto *et al* (2020) used optical phase-shifting

interferometry in their tests. Their research showed that accurate calibration with this

technique improved the accuracy of pest monitoring systems by ensuring that the microphones' frequency response closely matched the optimal frequency ranges for identifying insect-related sounds.

Temperature compensation is another popular calibration technique. Because temperature variations can change the environment's acoustic characteristics and skew sensor data, Mello *et al.* (2021) concentrated on how temperature variations affect sensor readings. In order to solve this, they created software algorithms that automatically modified the sensor's output in response to current temperature readings, increasing the precision of the data gathered under various environmental circumstances.

Changes in air pressure and humidity can also affect sensor sensitivity, particularly outside. The necessity of calibrating MEMS sensors under various pressure and humidity conditions in order to maintain consistent performance was highlighted in a number of studies, including Kham *et al.* (2021). Successful pest identification in agricultural settings, where these factors are ever-changing, depends on the sensors operating at their best in every situation.

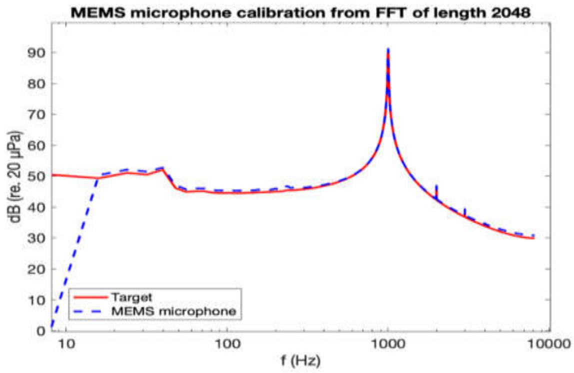

Figure 4 - MEMS sensor calibration. Adapted from Ishikawa K., Yatabe K., Oikawa Y., 2020. Determination of frequency response of MEMS microphone from sound field measurements using optical phase-shifting interferometry method. Appl Acoust. 2020;168:107523.

4.4.2. Sensor evaluation methods

Assessing the sensor's performance comes next after calibration is finished. The accuracy, sensitivity, and signal-to-noise ratio (SNR) of the sensor are evaluated using a number of critical criteria. Accuracy, which gauges how closely the sensor's data match the actual pest-related sound signature, is one of the most widely utilized criteria. To validate the sensor data, many research included ground truth data, such as visual pest identification or manual insect counts. To reduce false positives, Opprud Jakobsen *et al.* (2022) cross-validated the sensor's real-time insect sound detection capabilities using manual eye inspection in addition to sensor readings.

The signal-to-noise ratio (SNR), which is essential for differentiating insect noises from background noise, was a primary evaluation focus in numerous research. A high SNR enables the sensor to detect insect-related sounds precisely because agricultural areas are mostly noisy due to machinery, wind, and animal sounds. Zhang *et al.* (2020), for instance, isolated noises made by pests and filtered out unnecessary sounds using spectral analysis to assess the SNR. This method enhanced the sensor's overall performance in the actual environment.

Precision and recall are frequently employed as evaluation criteria in addition to accuracy and SNR to gauge a sensor's capacity to accurately identify pests while reducing false positives and false negatives. When testing their deep learning-based acoustic pest detection system, Kumar *et al.* (2021) used these measures to achieve a high recall, which ensures that the system correctly detects the presence of pests, and a high precision, which prevents false alarms.

4.4.3. Ground truthing and data verification

In sensor evaluation, the ground truthing procedure is essential. In order to confirm the correctness of the data, this method compares sensor outputs with established references, including visual observations or manual insect counts. Ground truthing was used in the Riede *et al.* (2021) study to validate the identification of tropical insect pests under various environmental circumstances. The acoustic sensors were accurately detecting pests with the help of the ground truthing technique, and any inconsistencies in the data were noted for additional examination.

In order to create training datasets for machine learning models, which were utilized to categorize insect sounds, ground truthing is also helpful. Research such as Nagaraj *et al.* (2022) demonstrated how they trained convolutional neural networks (CNNs) for precise pest detection using ground-truth data. The researchers increased the model's accuracy and resilience by comparing it to manual observations.

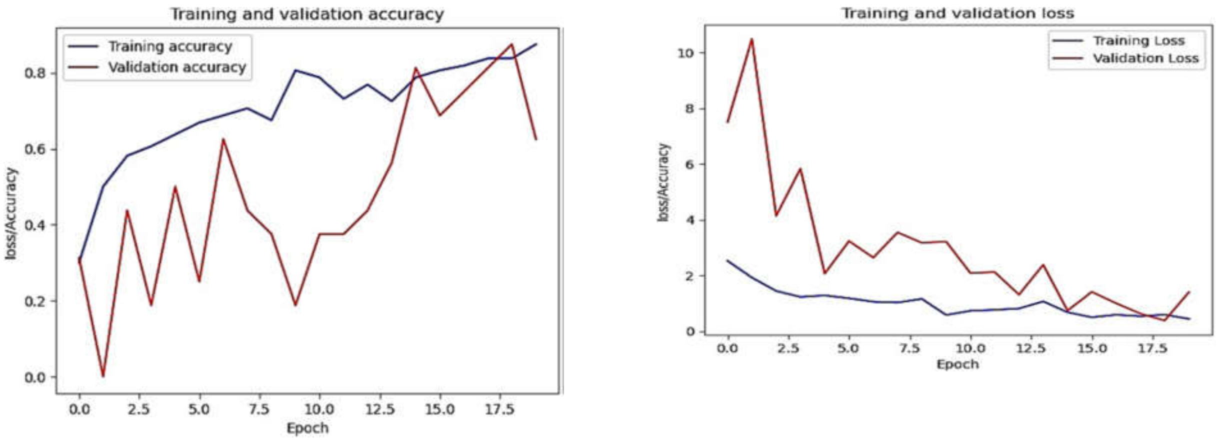

***Figure 5**:* Training and validation accuracy

4.4.4.Challenges in calibration and evaluation

Calibration and evaluation are necessary to achieve reliable sensor performance, but some challenges remain. Sensor drift is a major issue that arises when environmental conditions or sensor degradation led to the progressive loss of calibration over time. This is particularly problematic for long-term monitoring systems used in agricultural fields. Self-calibration methods were used by Mello *et al.* (2021) and Opprud Jakobsen *et al.* (2022) to overcome this, allowing the sensor system to sustain accuracy automatically over time.

The evolving nature of pest sound features presents another difficulty. The frequency at which pests emit noises varies depending on their species, stage of life, and activity. It may therefore be difficult to calibrate sensors to detect a wide range of frequencies. Riede *et al.* (2021) investigated this problem by employing multi-frequency MEMS microphones, which may be able to identify a greater variety of pest species and behaviours by encompassing a larger spectrum of aural signals. To distinguish between species-specific sounds, however, more advanced data processing methods were needed.

4.5. Challenges and limitations

4.5.1. Environmental challenges

Acoustic data gathering may be hindered by the unpredictability of agricultural surroundings, which frequently have fluctuating weather patterns and levels of background noise. According to research by Bieganowski *et al.* (2022) and Kham *et al.* (2021 Wind and rain generate background noise that interferes with and masks the low-frequency signals emitted by pests. Furthermore, variations in humidity and temperature might impact MEMS microphone sensitivity and calibration, decreasing the precision of pest detection systems.

4.5.2. Sensor sensitivity and signal range

MEMS microphones' detection capabilities rely on their capacity to pick up minute sounds produced by pests. According to several research, like Hermawanto *et al.* (2022), some pests generate sound frequencies that are too high for typical MEMS sensors to detect, hence professional equipment is required. Furthermore, a dense network of devices is needed to cover broad fields due to the restricted range of individual sensors, which raises the complexity and cost of the system.

4.5.3. Data processing and complexity of the algorithm

To distinguish insect sounds from background noise in the vast datasets generated by acoustic sensors, strong signal processing and machine learning methods are needed. For instance, Kumar *et al.* (2021) employed deep learning techniques to improve detection, but they noted that this came at a significant computational expense. Real-time data processing is challenging in resource-constrained environments because devices must operate efficiently without compromising accuracy.

4.5.4. Financial limits and accessibility

Even if the cost of acoustic pest monitoring systems has decreased, small-scale farmers may still find it prohibitively expensive to integrate sophisticated sensors, wireless communication modules, and processing resources. Mahbub *et al.* (2021) acknowledged the trade-offs between affordability and system performance while investigating cost-effective options.

4.5.5. Longevity and maintenance

Sensor performance may deteriorate over time due to the severe circumstances they are exposed to when deployed outdoors, such as dust, moisture, and physical impacts. In order to guarantee long-term dependability, studies by Jakobsen *et al.* (2022) and Ozevin *et al.* (2022) emphasize the significance of creating robust sensor designs and self-diagnostic features. Frequent upkeep, including battery replacement and recalibration, increases operational costs that may discourage broad use.

5. FINDINGS AND DISCUSSION

Numerous studies have contributed to the development of acoustic pest monitoring utilizing MEMS microphones in agricultural applications. We can infer about the effectiveness, constraints, and potential future paths of these technologies in pest detection by examining the results.

5.1.Trends in acoustic pest detection

As is common, the research uses low-frequency sound waves generated by insect movements, feeding activities, and communication signals. According to Bieganowski *et al.* (2022) and Kham *et al.* (2021), accurate identification of these noises requires complex filtering techniques in order to distinguish between environmental disturbances and noise produced by pests. Because of its small size, low power consumption, and ease of integration with other wireless technologies like IoT and LoRa, MEMS microphones are growing in popularity. Their affordability and sensitivity are praised.

Research by Bhairavi *et al.* (2022) and Kumar *et al.* (2021) investigated the incorporation of deep learning techniques for acoustic signal processing in real time. The goal of these methods is to increase classification accuracy, particularly in noisy, complicated situations. Convolutional neural networks (CNNs) were used by Kumar *et al.* (2021) to improve the accuracy of pest identification, especially in large agricultural areas where ambient noise is a significant obstacle. The deep learning-enabled systems performed noticeably better than conventional models, highlighting how crucial it is to use AI in order to efficiently handle big datasets.

5.2. Comparative analysis of methods

While Kham *et al.* (2021) focused on MEMS sensors for sound level monitoring, others, like Azfar *et al.* (2022) and Sindhura Bhairavi *et al.* (2022), preferred wireless sensor networks. These studies have demonstrated that deploying multiple sensors across a wide area enhances detection capabilities compared to using a single sensor. Another advantage of wireless sensor networks (WSNs) is scalability, which makes it possible to monitor vast agricultural plots in real time without using a lot of cable. Yet, there are certain obstacles to MEMS sensors' efficacy in pest monitoring. Ozevin *et al.* (2022) emphasized how MEMS devices' performance might be impacted by external variables like temperature and humidity. Given that weather conditions frequently change in the field, this constraint has been a major worry.

Sensing Technologies	Range	Accuracy	Cost	Outdoor Performance	Sensitivity	Complexity of Support Electronics
Acoustic	Medium	Medium	Low	Medium	Medium	Medium
Optical	Medium	Medium	Medium	Medium	Medium	Low
Laser	High	High	High	High	High	Low
Ultrasonic	High	High	Medium	High	High	Medium

Table 1: Sensing technologies and their characteristics

5.3.Applications in pest management

Precision agriculture's use of these acoustic monitoring tools is still developing in practice. Using cloud platforms and mobile apps, Mahbub et al. (2021) and Ting et al. (2022) investigated the use of IoT-based systems that offer useful insights in addition to pest identification. Real-time pest control automation is made possible by the combination of sound sensors and data analytics systems. For example, depending on the information gathered by the sensors, systems may initiate autonomous pest management procedures, such as releasing natural predators or turning on particular spray systems.

By incorporating edge computing to process data locally, Kumar *et al.* (2021) shown how these systems may be further enhanced, lowering latency and facilitating prompt pest diagnosis and action. These advancements have the potential to greatly reduce the need for manual monitoring, increasing the overall effectiveness of pest control.

5.4. Areas of further study

Subsequent studies can focus on developing hybrid pest monitoring systems that use environmental and optical sensors in addition to acoustic ones. These hybrid systems could increase system reliability, decrease noise from non-pest sources, and improve accuracy. Predicting pest activity more accurately may also be possible with the use of machine learning models created for real-time analysis.

Another major problem is making these technologies scalable and inexpensive. The development of low-cost, energy-efficient equipment will enable the public, particularly small-scale farmers, to utilize open-source platforms for pest-monitoring technologies. This would bridge the gap between cutting-edge technology and its more practical use on farms worldwide.

Technology/ Method	Acuuracy (%)	Cost	Scalability	Challenges	References
MEMS microphone	85-90	Low	High	Environmenta noise interference	Bhairavi et al., 2022
IOT-Integrated sytems	88-92	Medium	Moderate to high	Data reliability in adverse environments	Prakash et al., 2021
Machine Learning algorithms	90+	Medium	Moderate	Limited annotated datasets	Kumar et al., 2020
Hybrid systems	90+	High	Very high	High setup cost, complex integration	Prakash et al., 2021

Table 2 - Summary of the comparative performance of various pest detection technologies.

6. CONCLUSION

The incorporation of acoustic sensors and new sensor-based technologies into pest control and detection is a milestone in the modern agriculture. As Bieganowski *et al.* (2020) illustrate, outdoor insect monitoring systems are the key to the effective detection of pest activity in arable crops, facilitating real-time minimization of infestation. Kham *et al.* (2021) and Azfar *et al.* (2023) also illustrated the use of wireless sensor networks and MEMS-based sound level monitoring, showing their adequacy for agricultural settings. The technologies not only enhance accuracy and operational effectiveness but also provide more sustainable and eco-friendly alternatives to conventional pest management strategies.

A close reading of several studies shows the application of acoustic sensors and machine learning algorithms to be a highly promising solution for the accurate detection of pests in a range of crops. Bhairavi *et al.* (2022) and Kumar *et al.* (2021) cited the role of deep learning in enhancing detection accuracy, with the clear trend being the application of artificial intelligence (AI) and acoustic monitoring systems. Mahbub *et al.* (2021) and Prakash *et al.* (2023) study, however, cite the role of wireless communication and the Internet of Things (IoT) in enhancing scalability and flexibility, making these technologies more adaptable to large-scale farming practices. In spite of these innovations, there are certain challenges to be overcome, mainly in terms of affordability, adaptability and resilience to environmental noise. To mitigate these limitations, the application of more than one type of sensor such as optical, environmental, and hybrid sensor systems can be employed to improve the detection accuracy and minimize false positives. Also, the cost and longevity of these technologies must be optimized to facilitate their mass adoption, particularly by small-scale farmers across the world. Initiatives to develop open-source, low-cost pest monitoring systems operated using renewable energy sources like solar panels, can make these technologies more accessible. Collaboration among researchers, policymakers, and the farming community is also necessary to develop standardized datasets and augment AI-based detection models.

In summary, sensor-based pest monitoring is an emerging technology with a great potential to transform pest management practices. These constraints like cost, reliability, and versatility are crucial to be overcome to obtain the greatest benefits of the model proposed. With advancements in technology and inter-disciplinary research, such technologies can transform agriculture globally, making pest management more effective, targeted, and sustainable in the upcoming years.

7. ETHICS DECLARATION

The authors declare no conflicts of interest. All methods used in this study comply with relevant guidelines and ethical standards.

8. DATA AVAILABILITY

The authors declare no conflicts of interest. All methods used in this study comply with relevant guidelines and ethical standards.

9. REFERENCES

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